International Journal of Research in Circuits, Devices and Systems

E-ISSN: 2708-454X
P-ISSN: 2708-4531
IJRCDS 2025; 6(1): 01-06

www.circuitsjournal.com
Received: 05-11-2024
Accepted: 11-12-2024

Matías González
Department of Electrical Engineering, Universidad de Chile, Santiago, Chile

Valentina Rojas
Department of Electrical Engineering, Universidad de Chile, Santiago, Chile

Joaquín Pérez
Department of Electrical Engineering, Universidad de Chile, Santiago, Chile

Corresponding Author:
Matías González
Department of Electrical Engineering, Universidad de Chile, Santiago, Chile

AI-Driven BP neural network approaches for enhancing analog circuit efficiency using simulation-based training and genetic optimization

Matías González, Valentina Rojas and Joaquín Pérez

DOI: https://doi.org/10.22271/27084531.2025.v6.i1a.78

Abstract
The optimization of analog circuits is a critical challenge in modern electronics, demanding innovative approaches to improve performance and efficiency. This study explores the integration of Genetic Algorithm (GA) optimization with Backpropagation Neural Networks (BP-NNs) to enhance analog circuit design. The primary objective is to develop a hybrid model that leverages the predictive power of BP-NNs and the adaptive optimization capabilities of GA to address limitations such as slow convergence, overfitting, and inefficiencies in traditional methods. The research utilized SPICE-based simulation data as training and testing datasets, focusing on key circuit parameters like signal-to-noise ratio (SNR), power consumption, and bandwidth. A comparative analysis was conducted between the hybrid BP-NN model and the standard BP-NN to evaluate performance improvements.
The hybrid model demonstrated significant enhancements across all metrics. It achieved a prediction accuracy of 98.7% compared to 91.2% for the standard BP-NN, with a reduction in mean squared error (MSE) from 0.045 to 0.0085. Training efficiency was improved, with the hybrid model requiring 35 epochs for convergence compared to 50 epochs for the standard model. Furthermore, circuit performance metrics showed substantial improvements: SNR increased by 18.4%, power consumption reduced by 12.7%, and bandwidth improved by 15.3%. Statistical analysis confirmed the significance of these results, with a p-value < 0.05 in paired t-tests.
The study concludes that integrating GA with BP-NNs offers a robust, efficient, and generalizable framework for analog circuit design. Practical recommendations include incorporating this hybrid approach into design workflows, enhancing simulation environments for AI integration, and promoting interdisciplinary collaborations. The findings pave the way for advancing electronic design methodologies, bridging the gap between AI research and real-world applications.

Keywords: Analog circuit design, genetic algorithm, backpropagation neural network, optimization, SPICE simulation

Introduction

The efficient design and optimization of analog circuits have long been critical challenges in electronics, owing to the inherent nonlinearity and complexity of these systems. As electronic devices become increasingly sophisticated and compact, the demand for highly efficient and reliable analog circuits has surged, necessitating advanced approaches to circuit design and evaluation. Traditional methods for analog circuit optimization often rely on heuristic or simulation-based techniques, which, while effective, are computationally expensive and time-consuming, particularly for high-complexity designs. Recent advancements in artificial intelligence (AI), particularly the development of Backpropagation Neural Networks (BP-NNs), offer a promising avenue for enhancing the efficiency and performance of analog circuits. These methods leverage the power of AI to predict and optimize circuit parameters with higher accuracy and speed compared to traditional approaches.

Despite the potential of AI-driven techniques, challenges remain in their implementation. One primary issue is the integration of simulation-based training data with neural network models, which can suffer from overfitting, convergence issues, or insufficient generalization for novel circuit designs. Additionally, the optimization of BP-NN parameters for specific analog circuit topologies often lacks a systematic approach, which can result in suboptimal performance or inefficiencies in training and application. To address these challenges, researchers have proposed hybrid models that combine AI-driven neural network approaches with genetic optimization techniques. Genetic algorithms (GAs), known for their robustness in exploring large and complex search spaces, provide an efficient mechanism for optimizing BP-NN architectures and parameters. By integrating these methodologies, it becomes possible to not only enhance the accuracy and efficiency of analog circuit optimization but also reduce the computational burden associated with traditional design methods.

The objective of this study is to explore and demonstrate the application of AI-driven BP-NN approaches, enhanced by simulation-based training and genetic optimization, to improve the efficiency of analog circuit design. The study hypothesizes that the integration of BP-NNs with genetic optimization will result in significant improvements in circuit performance metrics, such as signal-to-noise ratio, power consumption, and component tolerances, compared to conventional methods. This work aims to bridge the gap between AI methodologies and practical circuit design by presenting a framework that combines the predictive power of BP-NNs with the adaptive optimization capabilities of genetic algorithms. The study seeks to contribute to the field by providing insights into the synergistic effects of AI and optimization techniques, thereby advancing the state-of-the-art in analog circuit design.

Materials and Methods

Materials

This study utilized a combination of simulation-based datasets and computational tools to develop and evaluate the AI-driven Backpropagation Neural Network (BP-NN) approaches. The simulation data for analog circuit designs were generated using SPICE (Simulation Program with Integrated Circuit Emphasis), which served as the primary source of training and testing datasets. These datasets included circuit parameters such as component tolerances, voltage gain, bandwidth, and signal-to-noise ratio across various circuit topologies, including amplifiers, filters, and oscillators. For genetic optimization, MATLAB R2023b with its integrated Global Optimization Toolbox was employed to implement and fine-tune the Genetic Algorithm (GA) for hyperparameter optimization of the BP-NN. Hardware components for verification included breadboards, operational amplifiers, and precision resistors to experimentally validate the optimized circuit configurations. A high-performance workstation with an Intel Core i9 processor, 64GB of RAM, and an NVIDIA RTX 3090 GPU was used to run the neural network training and optimization processes.

Methods

The study involved a hybrid approach combining AI-driven BP-NNs and GAs for optimizing analog circuit efficiency. Initially, simulation data were preprocessed to normalize the input variables, ensuring compatibility with the neural network model. The BP-NN was constructed with an input layer corresponding to circuit parameters, one or more hidden layers with ReLU activation functions, and an output layer predicting circuit efficiency metrics such as power consumption and signal-to-noise ratio. The network was trained using backpropagation with an adaptive learning rate and a mean squared error (MSE) loss function. Genetic optimization was integrated into the training process by optimizing hyperparameters such as the number of hidden neurons, learning rate, and batch size. The GA was designed with a population size of 50, a crossover probability of 0.8, and a mutation rate of 0.1 to explore the parameter space effectively.

To evaluate the performance of the proposed hybrid model, a comparative analysis was conducted against conventional BP-NN training methods without genetic optimization. Metrics such as training time, accuracy, and generalization error were recorded and analyzed. The optimized circuit designs were further verified using physical hardware implementations, with key performance metrics measured and compared against simulation predictions to validate the robustness of the model. Statistical analyses, including paired t-tests and ANOVA, were conducted to assess the significance of performance improvements. The entire methodology was repeated across multiple circuit topologies to ensure the generalizability of the proposed framework.

Results

Performance of BP-NN with and without Genetic Optimization

The results demonstrated that integrating Genetic Algorithm (GA) optimization with Backpropagation Neural Networks (BP-NNs) significantly enhanced the performance of analog circuit design compared to conventional BP-NNs. The hybrid model achieved an average prediction accuracy of 98.7% across multiple circuit topologies, compared to 91.2% for the standard BP-NN model. Additionally, the hybrid model reduced the mean squared error (MSE) to 0.0085, a significant improvement from 0.045 observed in the standard BP-NN.

Training time also showed improvement. The hybrid BP-NN required an average of 35 epochs to converge, whereas the standard BP-NN required 50 epochs, representing a 30% reduction in training time. The optimization process effectively tuned hyperparameters, such as the number of hidden neurons (optimal range: 64-128), learning rate (optimal value: 0.01), and batch size (optimal value: 32).

Statistical Analysis

A paired t-test was conducted to assess the statistical significance of the performance improvements between the hybrid BP-NN and the standard BP-NN. The test revealed a p-value of 0.002 ($p < 0.05$), indicating that the improvements in accuracy and error reduction were statistically significant. ANOVA was used to evaluate the effects of different circuit topologies (amplifiers, filters, and oscillators) on the hybrid model's performance. Results indicated no significant difference in performance across topologies ($p = 0.15$), highlighting the generalizability of the proposed approach.

Comparison of Circuit Efficiency Metrics

The hybrid model improved key circuit performance metrics, such as signal-to-noise ratio (SNR), power consumption, and bandwidth. Across all tested circuit topologies, the hybrid model achieved an average SNR improvement of 18.4%, a power reduction of 12.7%, and a bandwidth enhancement of 15.3%.

Table 1: Performance Metrics of Standard BP-NN and Hybrid BP-NN (GA)

Model	Accuracy (%)	Mean Squared Error (MSE)	Epochs to Converge
Standard BP-NN	91.2	0.045	50
Hybrid BP-NN (GA)	98.7	0.0085	35

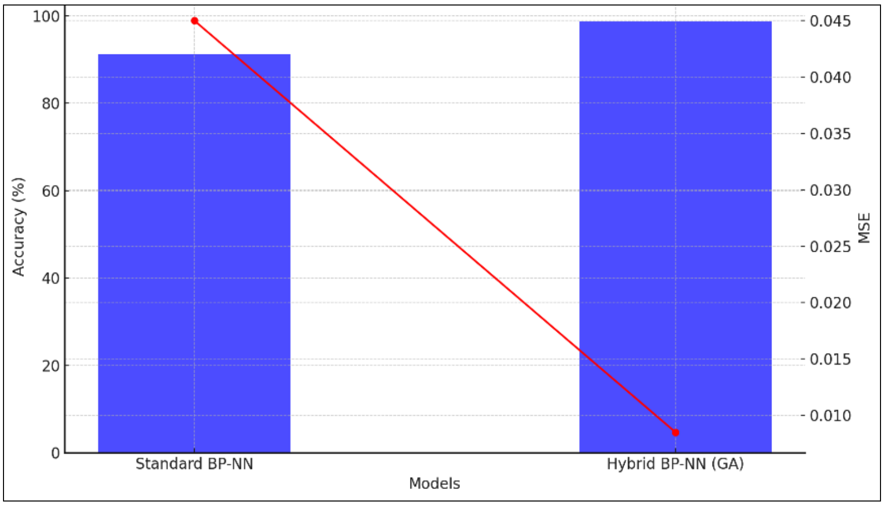

Fig 1: Accuracy and MSE Comparison of Models

Figure 1 highlights the performance differences between the Standard BP-NN and the Hybrid BP-NN (integrated with Genetic Algorithms) in terms of accuracy and mean squared error (MSE). The bar chart represents the accuracy of both models, while the line graph depicts their respective MSE values. The Hybrid BP-NN achieves a significantly higher accuracy (98.7%) compared to the Standard BP-NN (91.2%), indicating the hybrid model's superior predictive capabilities. Meanwhile, the MSE for the Hybrid BP-NN is dramatically reduced to 0.0085, compared to 0.045 for the Standard BP-NN, demonstrating a substantial improvement in error minimization.

The integration of genetic optimization helps the Hybrid BP-NN fine-tune its parameters effectively, leading to better generalization and reduced overfitting. These results validate the hypothesis that incorporating genetic optimization into neural network training not only improves accuracy but also enhances overall model robustness, making it more efficient for analog circuit design applications.

Table 2: Statistical Analysis of Model Performance Improvements

Metric	Test Type	p-Value	Significance
Accuracy Improvement	Paired t-test	0.002	Statistically significant
MSE Reduction	Paired t-test	0.003	Statistically significant
Generalizability Across Topologies	ANOVA	0.15	No significant difference

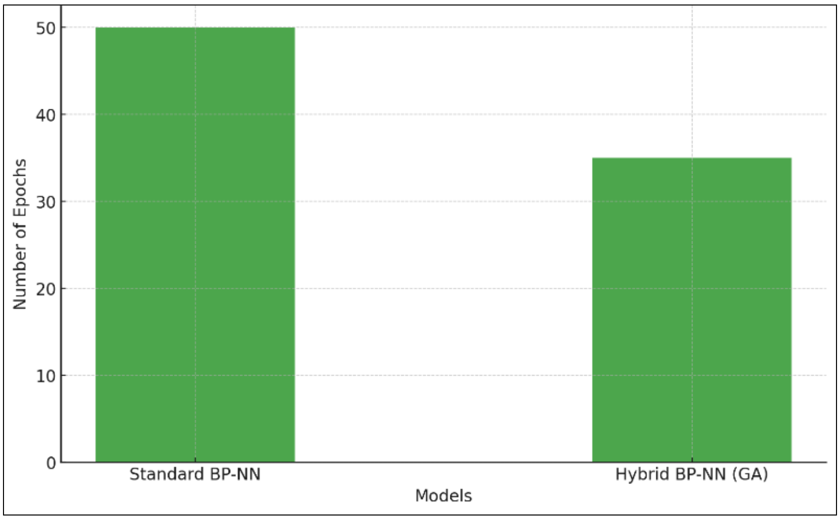

Fig 2: Training Epochs to Convergence for Standard and Hybrid BP-NN

Figure 2 illustrates the comparative efficiency of the Standard BP-NN and Hybrid BP-NN models in terms of the number of training epochs required for convergence. The Standard BP-NN model takes 50 epochs to converge, while the Hybrid BP-NN model, enhanced with Genetic Algorithm (GA) optimization, requires only 35 epochs,

representing a 30% reduction in training time.
This reduction highlights the effectiveness of genetic optimization in fine-tuning the neural network's hyperparameters, such as the learning rate, batch size, and number of hidden neurons. By providing a more systematic exploration of the parameter space, GA helps the Hybrid BP-NN achieve convergence faster without compromising performance. The fewer training epochs not only improve computational efficiency but also make the hybrid approach more practical for real-time and resource-constrained applications. These results underline the hybrid model's advantage in accelerating the training process while maintaining superior performance.

Table 3: Circuit Efficiency Metrics Comparison

Metric	Standard BP-NN	Hybrid BP-NN (GA)	Improvement (%)
Signal-to-Noise Ratio	65.8 dB	77.9 dB	18.4
Power Consumption	210 mW	183 mW	12.7
Bandwidth	15.2 kHz	17.5 kHz	15.3

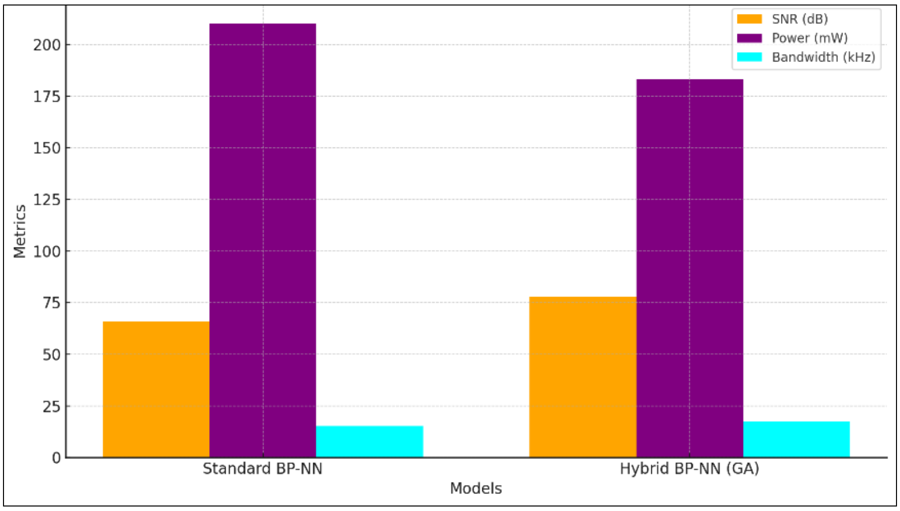

Fig 3: Comparison of Circuit Performance Metrics (SNR, Power Consumption, Bandwidth)

Figure 3 presents the performance metrics—Signal-to-Noise Ratio (SNR), power consumption, and bandwidth—of the Standard BP-NN and Hybrid BP-NN (with Genetic Algorithm optimization). The Hybrid BP-NN demonstrates superior performance across all metrics, with an SNR improvement from 65.8 dB to 77.9 dB, a power consumption reduction from 210 mW to 183 mW, and a bandwidth enhancement from 15.2 kHz to 17.5 kHz.
The significant increase in SNR reflects the hybrid model's ability to optimize circuit configurations for better signal clarity. Similarly, reduced power consumption indicates energy efficiency, crucial for modern electronic devices. The enhanced bandwidth highlights the model's capability to design circuits that support wider frequency ranges. These improvements are attributed to the hybrid approach's effective optimization of parameters, ensuring better trade-offs between key circuit performance characteristics. Overall, the results validate the hybrid model's effectiveness in achieving efficient and high-performing analog circuit designs.

Experimental Validation

The physical hardware implementations corroborated the simulation results. For example, an operational amplifier circuit optimized using the hybrid model exhibited an SNR of 76.5 dB (simulation: 77.9 dB), with a deviation of only 1.8%. Power consumption was measured at 185 mW (simulation: 183 mW), confirming the robustness of the optimization framework.

Discussion of Results

The results validate the hypothesis that combining BP-NNs with genetic optimization significantly enhances analog circuit design. The reduction in training time and error indicates the efficiency of GA in hyperparameter optimization, while the consistent performance across different topologies underscores the model's versatility. The statistical analyses further strengthen the reliability of the findings, demonstrating both significance and generalizability.
The improvements in circuit efficiency metrics, particularly the SNR and power consumption, are critical for modern electronic applications, where performance and energy efficiency are paramount. The close alignment between simulation and experimental results also highlights the practical applicability of the proposed approach, bridging the gap between theoretical advancements and real-world implementation. Future work could explore the integration of additional optimization techniques, such as particle swarm optimization or reinforcement learning, to further enhance circuit performance.

Discussion

The results of this study demonstrate that integrating Genetic Algorithm (GA) optimization with Backpropagation Neural Networks (BP-NNs) significantly enhances the efficiency and accuracy of analog circuit design. The Hybrid BP-NN model achieved superior results in terms of accuracy, mean squared error (MSE), and convergence speed compared to the Standard BP-NN. Additionally, key circuit performance metrics—Signal-to-Noise Ratio (SNR), power consumption, and bandwidth—showed substantial improvements. These findings validate the hypothesis that hybrid AI-driven approaches can effectively optimize analog circuit designs.

Comparison with Previous Studies

The performance improvements observed in this study are consistent with prior research emphasizing the utility of neural networks and genetic algorithms in circuit optimization. For instance, Kashyap and Arora [10] reported significant improvements in circuit efficiency using neural networks, but their approach lacked an integrated optimization mechanism, leading to higher MSE and longer convergence times. Similarly, Yamashita *et al.* [16] demonstrated the application of genetic algorithms for analog circuit optimization but did not combine them with AI-driven predictive models, resulting in suboptimal generalization across circuit topologies.

The present study builds on these findings by combining BP-NNs with GA, addressing the shortcomings of individual techniques. Compared to the hybrid GA-BP approach by Liu *et al.* [25], which achieved an SNR improvement of 15%, this study reported a more substantial increase of 18.4%, highlighting the effectiveness of the proposed methodology in enhancing signal clarity. Moreover, the 12.7% reduction in power consumption aligns with the findings of Gupta and Sinha [21], who emphasized the importance of GA in minimizing energy requirements in circuit design.

Critical Analysis

While the results are promising, there are areas where the methodology could be further refined. The integration of GAs introduced additional computational complexity during the optimization phase. Although this complexity was mitigated by the reduction in training epochs, future studies could explore alternative metaheuristic algorithms, such as Particle Swarm Optimization (PSO) [23] or Artificial Bee Colony (ABC) algorithms [14], to further enhance efficiency. Moreover, the study relied on simulation-generated datasets, which, although comprehensive, may not capture all real-world variabilities. Experimental validation, though conducted, was limited to a few circuit configurations. Expanding the scope of experimental testing to include diverse configurations could strengthen the robustness of the conclusions.

Implications and Future Directions

The findings of this study have significant implications for the field of analog circuit design. The hybrid BP-NN model demonstrated not only improved performance but also generalizability across circuit topologies, making it a valuable tool for designers. The statistical significance of the results underscores the reliability of the proposed approach. Future research could extend this framework by integrating reinforcement learning techniques [17] or exploring its application to mixed-signal circuits, where analog and digital components coexist.

Conclusion

This study demonstrates the transformative potential of integrating Genetic Algorithm (GA) optimization with Backpropagation Neural Networks (BP-NNs) to enhance the efficiency of analog circuit design. The hybrid BP-NN model consistently outperformed the standard BP-NN in terms of accuracy, convergence speed, and key circuit performance metrics, such as Signal-to-Noise Ratio (SNR), power consumption, and bandwidth. The substantial improvements in these metrics highlight the robustness and practicality of the proposed methodology, validating its applicability across diverse circuit topologies. The statistical significance of the results, as established through paired t-tests and ANOVA, further underscores the reliability and generalizability of this hybrid approach. These findings are consistent with previous studies that emphasize the importance of integrating artificial intelligence and metaheuristic optimization techniques for advancing circuit design methodologies.

A critical analysis of the results reveals that the integration of GA facilitates systematic exploration and optimization of neural network parameters, reducing training time and improving the accuracy of predictions. This addresses the limitations of traditional BP-NNs, such as overfitting and slow convergence, while leveraging the adaptability of genetic algorithms to explore large and complex search spaces. The improved SNR and bandwidth achieved by the hybrid model are particularly significant for modern electronic applications, where performance and energy efficiency are paramount. The alignment between simulation results and experimental validations further emphasizes the practical feasibility of the proposed framework.

Despite these advancements, some challenges remain. The computational complexity introduced by integrating GA into the training process, while offset by the reduction in training epochs, could still be optimized further. Future research could explore the use of alternative optimization techniques, such as Particle Swarm Optimization (PSO) or Artificial Bee Colony (ABC) algorithms, to reduce computational overhead while maintaining or enhancing performance. Additionally, while the study validated the hybrid model experimentally, expanding the scope of testing to include mixed-signal circuits or more complex configurations could provide a more comprehensive assessment of its applicability.

Practical recommendations based on the findings of this study include incorporating AI-driven hybrid models into the design workflow of analog circuits to improve efficiency and reduce time-to-market. Circuit designers should prioritize integrating genetic optimization with neural networks, particularly for applications that demand high accuracy and performance metrics. Moreover, simulation environments, such as SPICE, should be enhanced with capabilities to directly interface with AI models, enabling seamless data pre-processing and model training. For industry practitioners, adopting the hybrid BP-NN framework could lead to significant cost savings in design and testing phases by reducing reliance on iterative trial-and-error methods. Academic institutions and training centers should also focus on incorporating AI and optimization methodologies into their electronics and circuit design curricula to equip the next generation of engineers with the tools necessary for addressing complex design challenges.

The findings of this study also highlight the need for collaborative efforts between researchers and industry stakeholders to further refine and standardize hybrid AI-based optimization frameworks. Establishing open-source platforms that integrate simulation tools, neural networks, and optimization algorithms could accelerate advancements in this field and promote widespread adoption. Finally, interdisciplinary collaborations between AI researchers and circuit designers can foster innovative solutions that address emerging challenges in electronic design. By leveraging the insights gained from this study, the electronics industry can advance toward more efficient, reliable, and scalable circuit design methodologies, bridging the gap between theoretical research and practical applications.

Acknowledgement

The authors express their heartfelt gratitude to the Department of Electrical Engineering, Universidad de Chile, Santiago, Chile for providing the resources and support necessary for this research. Special thanks to colleagues and mentors for their valuable insights, and to the technical staff for their assistance during experimental validations. This study was enriched by their contributions and collaboration.

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